# RULE-BASED CLASSIFIERS AND META CLASSIFIERS FOR IDENTIFICATION OF CARDIAC AUTONOMIC NEUROPATHY PROGRESSION

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**Abstract**

We investigated and compared several rule-based classifiers and meta classifiers in their ability to obtain multi-class classifications of cardiac autonomic neuropathy (CAN) and its progression. The best results obtained in our experiments are significantly better than the outcomes published previously in the literature for analogous CAN identification tasks or simpler binary classification tasks.

Data mining is very important for health informatics and has been actively investigated, for example, in [3], [5] and [9]. In this article we investigated rule-based classifiers and meta classifiers. Our experiments compared the ability of the meta classifiers to obtain classifications of cardiac autonomic neuropathy progression for an extensive data set collected by the Diabetes Complications Screening Research Initiative (DiScRi) at Charles Sturt University.

Cardiac autonomic neuropathy (CAN) is a condition associated with damage to the autonomic nervous system innervating the heart and highly

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prevalent in people with diabetes, [1], [3], [5], [10]. It is known as one of the causes of mortality among type 2 diabetes patients. The problem of identifying CAN and CAN progression from ECG recordings has been discussed by [10] and [11]. Use of data mining and an extensive data base, which included several tests for CAN in addition to demographic and clinical features, was considered previously in [3], but due to lack of suitable data sets multi-class classifications of the progression of CAN have not been addressed. The classification of disease progression associated with CAN is important, because it has substantial implications for planning of timely treatment of people with diabetes. This paper uses the clinical test results and health-related parameters collected at the Diabetes Complications Screening Research Initiative, DiScRi, organised at Charles Sturt University [4] .

Rule-based classifiers and meta classifiers were trained to recognize four classes of CAN given in the data base (see Tables 1 and 2). The readers are referred to [10] for background information (see also [6], [7] and [14]). Ten-fold cross validation was applied to determine the effectiveness of these classifiers. Early CAN is traditionally measured using the Valsalva manoeuvre (VAHR), deep breathing (DBHR), and hand-grip (HGBP) tests. QRS width has also been shown to be indicative of CAN [1] and is included here. Our experimental results are presented in Tables 1 and 2.

| | Accuracy | Precision | Recall | ROC area |
|---|---|---|---|---|
| ConjunctiveRule | 65.13 | 0.536 | 0.651 | 0.717 |
| DecisionTable, DT | 76.98 | 0.781 | 0.770 | 0.899 |
| DTNB | 76.97 | 0.779 | 0.769 | 0.896 |
| FURIA | 85.07 | 0.856 | 0.851 | 0.917 |
| JRip | 81.83 | 0.818 | 0.818 | 0.881 |
| NNge | 89.53 | 0.896 | 0.895 | 0.918 |
| PART | 88.99 | 0.891 | 0.890 | 0.933 |
| Ridor | 83.53 | 0.836 | 0.835 | 0.871 |

**Table 1.** Rule-based classifiers for CAN progression

Table 2 contains outcomes of meta classifiers for the best base classifiers.

| Meta classifiers | Base classifiers | | | | | |
|---|---|---|---|---|---|---|
| | DT | FURIA | JRip | NNge | PART | Ridor |
| AdaBoost | 76.98 | 85.07 | 90.30 | 89.99 | 91.22 | 87.96 |
| Bagging | 82.45 | 89.15 | 86.68 | 89.92 | 90.99 | 87.53 |
| Decorate | 78.91 | 85.07 | 84.45 | 89.20 | 89.53 | 84.30 |
| Grading | 77.98 | 85.30 | 82.99 | 89.61 | 88.99 | 83.53 |
| MultiBoosting | 78.29 | 85.07 | 86.91 | 89.92 | 91.61 | 86.43 |
| Stacking | 78.68 | 84.68 | 82.90 | 89.61 | 88.22 | 83.53 |
| AdaBoost+Bagging | 91.53 | 90.92 | 88.47 | 90.15 | 91.30 | 91.15 |

**Table 2.** Meta classifiers based on rules for CAN progression

The best outcomes were obtained by the MultiBoosting based on PART classifier. These outcomes are significantly better than the results published previously in the literature for analogous CAN identification even for simpler binary classification tasks in [3].

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